In Good and in Bad Times? The Relation between Anomaly Returns and Market States

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Abstract

We evaluate the relation between the size of 138 return anomalies and market states using a sample of 56 countries from 1981 to 2019. We find that the vast majority of anomalies (51 of 138 statistically significant at the 5% level) perform better if the country's stock market index trades below its 200-day moving average, our definition of a bad market state; 10 anomalies perform significantly better in good market states. On average, the value-weighted four-factor alpha amounts to 46.7 (31.2) bps per anomaly-month in bad (good) times. In relative terms, abnormal anomaly returns are 49.8% higher in bad times. Our findings are consistent across regions and different anomaly classifications. They are robust to alternative market state classifications and additional controls for investor sentiment. The evidence suggests that risk or data-mining cannot entirely explain anomaly returns.

Keywords: Anomalies; international stock markets; market states; sentiment; market efficiency.

JEL classifications: G12, G14, G15.

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1. Introduction

Why do we observe so many abnormal return patterns (also known as anomalies or factors) in financial markets? Finding a satisfactory answer to this question has become a central research field in financial economics at least since John Cochrane's description of the current situation as a "zoo of new factors" in his 2010 presidential address to the American Finance Association (Cochrane, 2011). There are three competing explanations for the anomaly puzzle: risk, mispricing, and data-mining.

According to the risk-based explanation, abnormal returns are a compensation for bearing systematic, yet undefined risk. The risk-based explanation is consistent with the view that there are only few investors "who shouldn't act as if markets are efficient."[1] In contrast, the mispricing hypothesis relies on the idea that "the price is often wrong, and sometimes very wrong" (Thaler, 2017, p. 252). According to the mispricing hypothesis, abnormal returns are a manifestation of bounded investor rationality and limits-to-arbitrage, which prevent sophisticated market participants from (fully) eliminating anomalies. Finally, the argument of the data mining hypothesis is that the increased search for anomalies has also led to an increase in (spurious) discoveries: "Given the plethora of factors, and the inevitable data mining, many of the historically discovered factors would be deemed significant by chance." (Harvey et al., 2016, p. 45)

Supportive evidence exists for all three potential causes of anomalies, and in fact, they are not mutually exclusive. Nevertheless, recent empirical work suggests that mispricing (e.g., McLean and Pontiff, 2016; Lu et al., 2017; Yan and Zheng, 2017; Bartram and Grindblatt, 2018; Engelberg et al., 2018; Chen and Zimmermann, 2020; Jacobs and Müller, 2020) and data mining (e.g., Harvey et al., 2016; Chordia et al., 2017; Harvey, 2017; Linnainmaa and Roberts, 2018; Hou et al., 2020; Chordia et al., 2020; Harvey and Liu, 2021) are currently most often relied upon to explain the "factor zoo."

In this paper, we add to the ongoing debate by studying cross-sectional anomaly returns, i.e., long-short portfolio returns based on stock characteristics like firm size, book-to-market equity, momentum, etc., separately for good and bad times. Our analysis is based on a large data set of 138 return anomalies across 56 international equity markets from 1980 to 2019. We separate good times from bad times by focusing on the current state of the market. Specifically,

[1] Eugene Fama, *Chicago Booth Magazine*, Interview 30th June, 2016 (https://review.chicagobooth.edu/).

like in Huang et al. (2017), we assume that the market is in a good (bad) state if the country's main stock index, valued at the end of the previous month, is trading above (below) its 200-day moving average (MA).

As we outline below, the 200-day MA indicator can be applied in real-time as a forward looking predictor of market states, whereas other measures of good and bad times such as recessions can only be determined retrospectively. Moreover, it is an intuitive indicator that is not only highly correlated with other measures of bad times such as recessions, but is also commonly used by chartists, financial analysts, and other market professionals to self-assess the current state of the market. As it relies on very basic market data, we can use it to identify good and bad times for all international equity markets without imposing additional data requirements.

It is interesting to study the performance of anomalies across market states, because the competing explanations for the anomaly puzzle, i.e., risk, mispricing, and data-mining, make different predictions about how anomalies should perform in good and bad times. To start with the latter explanation, if anomalies are the result of pure data-mining, we would expect to find no relation between abnormal anomaly returns and the state of the market, apart from some random significant results due to Type-I error. The reason is that according to this hypothesis, the data has been "mined" to discover significant alphas over the entire sample period, and not to establish significant alpha differences between good and bad times.

We randomly generate 1,000 anomalies that have a statistically significant alpha with regard to the Carhart (1997) asset pricing model during our sample period. Confirming our prediction that data-mined anomalies should be largely unrelated to market states once we account for Type-I error false discoveries, we find that only 78 (7.8%) of these fictitious anomalies perform differently across market states at a 5% level of statistical significance.[2] Half of the fictitious anomalies (39) have a significant positive slope with respect to the market state indicator, and the other half have a significant negative slope.

In contrast to the data-mining hypothesis, both the risk-based hypothesis and the mispricing hypothesis posit that the performance of anomalies is linked to market states. In a world of

[2]At the 5% level of significance, we would expect about five of out of 100 tested anomalies to display a statistically significant performance difference between market states. The higher number of 7.8% significant anomalies which we observe may be the result of random sample fluctuations as well as non-normally distributed return data. This empirically derived estimate serves as a reference under the null hypothesis that all anomalies are due to data-mining in our later analyses.

efficient markets, the abnormal return of a stock must reflect a compensation for systematic risk. According to consumption-based asset pricing theory, this compensation is driven by the covariance of the stock's payoff with marginal utility (Cochrane, 2005). In bad times like recessions, investors will consume less and be more cost-conscious. A stock that performs better in such bad times is therefore generally preferable over stocks that do not have this hedging property against consumption risk. Stocks that offer protection against bad times are hence expected to trade at higher prices and earn lower expected returns. Transferring this idea from the stock level to the portfolio perspective, risk-compensating anomaly portfolios are expected to perform better in good times. This is the compensation for the fact that these portfolios perform particularly poorly in bad times, when protection is needed the most.

While the risk-based hypothesis leads to predictions of higher anomaly returns in good market states, the predictions of the mispricing hypothesis are less clear-cut and depend on the underlying nature of the mispricing. In Daniel et al. (1998) model, overreaction-driven mispricing emerges from investor overconfidence and biased self-attribution. According to Gervais and Odean (2001), investors treat success and failure asymmetrically; a success supports the information and leads to increased confidence, while a failure does not necessarily lead to a corresponding reduction. Aggregate investor overconfidence should increase after periods of prolonged market gains because most investors are net long in stocks. In good times, they will attribute their success to their own selection skills rather than a favorable market environment, which increases their overconfidence further. It follows that anomalies arising from investor overconfidence should be stronger in good market states.

This line of reasoning is presented in Cooper et al. (2004) and Gao et al. (2018). The authors analyze the performance of a single anomaly (momentum; distress risk) in relation to the market state, and in both cases they find that the abnormal anomaly return is indeed higher in up-markets.[3] An up-market occurs if the country's main stock index increased over the previous years. Cooper et al. (2004) measure up-markets over the last three years, while Gao et al. (2018) refer to the last 12 months.

Even though risk and overreaction-driven mispricing predict higher anomaly returns in good times, anomalies that are caused by mispricing could also be higher in bad times if the underlying reason is underreaction to new information. The central characteristic of underreaction-

[3] Gao et al. (2018) use Moody's KMV rating data to measure default risk, which is not available to us. In our data set, the closest anomaly is the failure predictor of Campbell et al. (2008) for which we do not find a significant relation with market states.

based mispricing is that firm-specific information is only gradually impounded into security prices (Hong and Stein, 1999). Such information diffusion can be more gradual in times when news is generally less likely to be publicly disseminated. Since research indicates that "bad news travel slowly" (Hong et al., 2000, p. 267), for instance because firm managers are reluctant to publish negative information, one would expect that information diffusion is slower especially during bad times, during which the news tends to be rather negative.

In addition, prior studies show that investors may be subject to the Ostrich effect, which leads to a selective attendance to new information (Karlsson et al., 2005; Galai and Sade, 2006). During good times, investors are keen to collect and process information about their stock investments, whereas during bad times with falling stock prices they would rather "put their heads in the sand." The Ostrich effect therefore also implies a delayed information diffusion during bad times, and hence more pronounced profits to anomalies that are caused by investor underreaction.

On the basis of these predictions, we regress monthly abnormal anomaly returns on our market state indicator, which we denote as *GOOD TIMES*. In our baseline tests, we measure anomaly performance with respect to the Carhart (1997) four-factor model, and calculate anomaly returns as the difference between quintile (5) and quintile (1) value-weighted portfolios. For ten of the 138 anomalies in our sample (7.2%), the slope for *GOOD TIMES* is statistically significantly positive at the 5% level. In contrast, 51 anomalies (37.0%) have a statistically significantly negative slope for *GOOD TIMES*, implying that they have higher abnormal returns during bad times. For the remaining 77 anomalies (55.8%), there is no statistically significant relation.

In economic terms, the average abnormal anomaly return amounts to 46.7 bps in bad times, and 31.2 bps in good times, a difference of 15.5 bps. This suggests that anomaly strategies are on average 49.8% higher during bad times. We find that higher anomaly performance in bad times can be observed in all market regions, with the exception of frontier markets. Sorting single anomalies into categories, we observe the strongest relative performance gains in bad times for valuation-based anomalies, followed by analyst-based, fundamentals-based, and market-anomalies. Finally, the performance gain during bad times is mostly driven by the short side of the anomaly portfolio. The contribution of the long side is only 3.4%, whereas the contribution of the short side is 96.6%.

Our results have implications for the assessment of the "factor zoo." The high percentage of anomalies that have a statistically significant relation to *GOOD TIMES* is inconsistent with the data-mining hypothesis. In addition, the data-mining hypothesis is not able to explain the observed asymmetry of the effect with many more anomalies having a significant negative rather than positive relation to *GOOD TIMES*. However, our findings do not imply that data-mining is not a severe problem in anomaly research. There are 77 anomalies in our sample that display no relation to the state of the market, which may be consistent with data-mining. Nevertheless, our results suggest that it is unlikely that data-mining is the sole reason why there are so many anomalies identified in previous studies.

Our results are also not very supportive of the risk-based hypothesis. Many anomalies perform significantly better in bad times, suggesting that these anomalies are *less* risky from a consumption-based asset pricing perspective. It is also difficult to explain why the performance differential between good and bad times can be mainly attributed to the short side of the anomalies if risk is the underlying cause.

Interestingly, the factors of the Fama and French (1993) three-factor model, i.e., the market, size, and value factor, all have a statistically significantly positive coefficient for *GOOD TIMES*. This may serve as evidence that at least these "original" factors reflect a compensation for risk. The slope for momentum for *GOOD TIMES* is also positive at 1.09, which is statistically significant at the 0.1% level and indicates a more than 1% higher momentum return per month in favorable market conditions. This finding is consistent with the results for the U.S. stock market in Cooper et al. (2004). It could mean that momentum is a risk factor, or alternatively, that momentum is an overreaction phenomenon caused by overconfident investors, as argued in Cooper et al. (2004).

In contrast to risk, the mispricing hypothesis receives considerable more support in our empirical tests, because underreaction-based mispricing can arguably best explain why most anomalies are stronger in bad times. Mispricing coupled with limits-to-arbitrage, i.e., short-sale constraints, can also explain why the market state dependence is largely restricted to the short side of the anomaly. This does not imply that mispricing is the only reason for the anomaly puzzle. Nevertheless, the overall relation between anomalies and market states makes it difficult to argue that global stock markets are priced entirely in accordance with the efficient market hypothesis.

Our results contribute to several topics in the anomalies literature. First, we provide comprehensive insights on the applicability of different market state indicators and their cross-sectional relation to anomalies on an international basis. While we rely on the market state indicator with regard to the 200-day MA, similar to Huang et al. (2017), we also take into account a market state indicator based on the market movement over a three-year period (e.g., Cooper et al., 2004; Gao et al., 2018). In contrast to earlier work with a focus on specific factors or anomalies, like the market excess return, momentum, and distress risk, we study 138 factors/anomalies. Contrary to these prior studies, which find higher returns in positive market states, we observe that in the broad cross-section of anomalies, performance tends to be better in bad times.

Our study is also related to work on sentiment and anomalies (e.g., Stambaugh et al., 2012; Jacobs, 2015). These studies focus on the behavior of anomalies in periods of high and low investor sentiment according to the measure from Baker and Wurgler (2006). For the U.S. market, Miller (1977), Brav et al. (2010), and Hanson and Sunderam (2014), among others, find that due to limits to arbitrage, inefficiencies occur and anomalies are stronger following periods of high investor sentiment and this is mostly exhibited by the short side of the anomalies. We provide additional evidence by using other sentiment indicators, such as news sentiment or investor sentiment according to Schmeling (2009), and we conduct the analysis on an international basis. Interestingly, we find that the influence of sentiment on anomaly returns is highly dependent on the sentiment measure investigated. While our results for the Baker and Wurgler (2006) index in the U.S. market are consistent with prior studies, we observe a different relation between anomaly returns and the other sentiment measures internationally.

Finally. we provide further international evidence on the underlying causes of anomalies (e.g., Hou et al., 2011; Fama and French, 2012, 2017; Jacobs and Müller, 2020; Bartram et al., 2021; Bartram and Grindblatt, 2021). In general, anomalies are first observed for the U.S. market, and typically considered to compensate for risk or to reflect mispricing. Our evidence that many anomalies show meaningful return variation across market states suggests that their existence is universal across the globe.

Our paper is structured as follows. In Section 2 we describe the data, introduce the 200-day MA as our indicator for good times, and contrast it to alternative market state indicators, as well as sentiment measures. In addition, we discuss our methodology to select anomalies. In Section 3, we discuss our methodology and present our empirical findings. In Section 4, we provide the results from our robustness tests. We conclude in Section 5.

2. Data

2.1. Initial anomaly data

We use different Refinitiv databases to establish our anomaly database. We use Datastream to calculate stock returns and related measures, Worldscope for accounting information, and I/B/E/S for analyst information, such as earning forecasts. We follow the computational details in Jacobs and Müller (2018) to reconstruct 240 anomalies for our sample period. We add 10 anomalies to the data set following a further literature search. The resulting data set consists of 250 anomalies, calculated as the difference between quintile (5) and quintile (1) value-weighted portfolios.[4] These have a special relevance in research, since the return of the anomaly is not driven by small illiquid firms due to the weighting adjusted by the respective market capitalization. In addition, we include 20 factors from different asset pricing models. These are constructed according to their reference papers (e.g., 2x3 sorting for SMB and HML).

In the analysis, we incorporate data from September 1981 to June 2019 from 56 different countries, which are located in North America, Europe, and Asia Pacific; we also use emerging market data. Following the MSCI classification scheme, we group the countries as Developed Markets (DM), Emerging Markets (EM), and Frontier Markets (FM), which include 22, 22, and 12 countries, respectively. Our sample period from September 1981 to June 2019 is the maximum observable time series. For individual anomaly-country combinations the time series can be shorter, since data are not always available for such a long period, especially for EM and FM.

Furthermore, we randomly generate 1,000 anomalies to assess the data mining hypothesis. From the global stock universe, we sort the assets according to a uniform distribution. By country, we select the upper quintile (5) and lower quintile (1) of the assets to calculate a value-weighted global long-short portfolio return. We then determine whether the abnormal return of the resulting fictitious anomaly is significant at the 5% level with regard to the Carhart (1997) four-factor model. We iterate this process until 1,000 significant random anomalies are generated.

[4]We provide an overview of the investigated anomalies and the corresponding reference papers in Table A.1 of the Internet Appendix.

2.2. Market states

To define the market state, we mainly use the approach described by Huang et al. (2017). If the closing price of the country's main stock index (market index, MI) for the previous month $t-1$ is above (below) the last trading day's 200-day MA, we assume that the market is in a good (bad) state for month t. The *GOOD TIMES* indicator therefore acts as a real time indicator, since it can be calculated ex ante and no future information is necessary.

$$GOOD\ TIMES_{c,t} = \begin{cases} 1, & \text{if } \mathrm{MI}_{\mathrm{c,t-1}} > \mathrm{MA}_{\mathrm{t-1,200}} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

In Equation 1, the c subscript denotes the investigated country. For the country-specific market index, we use the total return index in USD, sourced from Datastream for December 1979 to June 2019 (e.g., TOTMKUS for U.S. or TOTMKBD for Germany).

An alternative to the *GOOD TIMES* indicator is the one used by Cooper et al. (2004), hereafter referred to as *UP*. If the country-specific market index increased in the past three years, the current month t is assumed to be an up-market or a good market state, respectively. If not, a bad market state is assumed. The data basis is the same as for *GOOD TIMES* to calculate the difference between the closing price of the market index for $t-1$ and $t-36$. For the further analysis, we use this indicator as an alternative to our main indicator, *GOOD TIMES*.

In contrast to the above mentioned market state indicators, a natural intuition is to set bad market states equal to recessions. In general, a recession is recognized after two consecutive quarters of negative GDP growth.[5] We follow this definition to construct a corresponding recession indicator that equals to 0 for a recession and is 1 otherwise to be in line with the previously introduced market state indicators.

Due to the definition, the use of this recession indicator to indicate bad market states has a disadvantage compared to the aforementioned market state indicators from an investor's perspective. The recession indicator is based on future values for GDP growth. This means that a recession can only be used retrospectively (ex post) to determine bad market states. For this reason, the recession indicator is merely a comparative parameter in our analysis.

The information for quarterly GDP growth (expenditure approach)[6] is deducted from OECD

[5] National Bureau of Economic Research, https://www.nber.org/.

[6] The recession indicator is calculated quarterly based on GDP growth, but we incorporate the values for

Stats for the period from 1947 to 2020. Intersected with the anomaly data set, GDP growth information is included for 38 OECD countries to calculate the recession indicator.

[Figure 1 about here.]

In Figure 1, we plot the time-series development of GDP growth and the resulting recession indication against the good times indicator for G7 countries. These are all included in our dataset of 56 countries. The figure shows that in many cases, *GOOD TIMES* reflects the expectation from the recession indicator and GDP growth, respectively. In addition, the longer-lasting phases of a recession or a decline in economic output are reflected by *GOOD TIMES*.

Nevertheless, whereas the recession indicator only shows sustained downturns in the economy, *GOOD TIMES* shows smaller gaps. These differences highlight potential advantages of using *GOOD TIMES* to identify bad market states. First, to be defined as a recession, there must be a decline in GDP over several months and be based on quarterly information, which allows a compensation across individual months. *GOOD TIMES* is updated monthly based on daily information. This makes the indicator much more flexible and reactive to short-term events in the economy. In addition, we observe a longer bad period according to *GOOD TIMES* for the first years of the 21st century, which is for most countries not indicated as a recession. This is mostly related to the burst of the dot-com bubble in 2000. The event mainly affected the technology sector and many investors had to absorb high losses. For the U.S. (see Figure 1a), GDP growth was reduced and just slightly negative. Since the decline was not sustainable, a recession was not indicated. The advantage of *GOOD TIMES* and *UP* is that they relate directly to the stock market. Thus, the underlying indexes directly reflect investor losses or gains and indicate market states from an investor's perspective.

[Table 1 about here.]

Taking into account the differences in Figure 1, the question arises how much the different market state indicators overlapp, i.e. agree in their assessment of a good/bad market state. In particular, Figure 1 shows that there are also discrepancies in the assignment of market states. To address this issue, in Table 1, we compare the allocations of *GOOD TIMES* and *UP* to the recession information. Although the National Bureau of Economic Research (NBER) publishes officially available information for the U.S. with respect to recessions, we further use

the whole quarter.

the reconstructed GDP growth-based recession indicator. The equivalence between the NBER recession indicator[7] and the recalculated indicator is 95.5%.

During our sample period, the majority of months are rated as a good market state for the U.S. and the other OECD countries, and this assessment holds for all considered indicators. Many of the months with bad market states relate to major historical events in the first decade of the 21st century, such as the collapse of the dot-com bubble in 2000 and the global financial crisis in 2007-2009 (e.g., for the U.S. see Figure A.1 in the Internet Appendix). For *GOOD TIMES*, we observe for the U.S. that about 77.6% (22.4%) of the months are characterized as a good (bad) market state. The other OECD countries have on average in 64.5% (35.5%) a good (bad) market state.

In addition, the second part of each panel shows the degree of coincidence between the market state indicators. The values indicate the percentage of assignments of the indicators that are in line with the result from the recession indicator. For the U.S., we see that with regard to *GOOD TIMES*, 81.3% (76.7%) of the good (bad) market state assignments are the same for the recession indicator. For the other OECD countries, there is on average an overall coincidence of 67.5%, as compared to the recession indicator and of 63.1% (68.5%) if *GOOD TIMES* indicates a good (bad) market state. Similar results are obtained for *UP*. Overall, the evidence shows that our definition of market states based on the 200-day MA is highly aligned with other fundamental-based indicators of good and bad times.

2.3. Sentiment

We include sentiment as a control metric. We employ the Baker and Wurgler (2006) sentiment index, which is a composite index combining six different proxies to form a measure of investor sentiment, looking at closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, equity share in new issues, and dividend premium.[8] Since this indicator is only available for U.S. market, we use it only as a supplemental measure.

In our main analyses, we use two alternative sentiment proxies that are internationally available. First, we concentrate on the sentiment proxy introduced by Schmeling (2009), hereafter referred to as *investor sentiment (S)*. The indicator is derived from country-specific consumer confidence surveys which focus on the consumption of private households. We follow

[7]We obtained the data from https://fred.stlouisfed.org/series/USREC (as of May 14, 2021).

[8]We take the data for *investor sentiment (BW)* from Jeffrey Wurgler's data library from July 1965 to December 2018.

the methodology of Schmeling (2009) and collect information on consumer confidence for 27 countries. Specifically, we obtain survey information for the U.S., New Zealand, Switzerland, Australia, and Japan from Datastream. The remaining 22 countries are European countries. The information for the European countries comes from surveys for the European Commission by the *Directorate Generale for Economic and Financial Affairs.*[9] If available, we use surveys with seasonal adjustments. For the U.S., New Zealand, and Australia, only values without seasonal adjustments are available. Since the surveys differ in the time horizon conducted or in the methodology used to calculate the seasonal adjustment, the use of surveys with and without adjustments has no effect on our analysis. In addition, we conduct a standardization of the distribution of the surveys for the individual countries, since the individual surveys contain different ranges of values and thus exhibit different standard deviations. Finally, our sample period mainly goes from January 1985 onwards, including gaps for some OECD countries.

Second, we use the Refinitiv MarketPsych database, which includes real-time news and social media information, to measure sentiment. A natural language processing engine generates scores based on various proxies, such as emotional indicators, macroeconomic metrics, ESG measures, and buzz metrics at the asset level. For our analysis, we use the combined version of news and social media information and refer to this as *news sentiment from MarketPsych (MP)*. The corresponding data set includes values from December 1997 onwards and covers 49 countries relative to the 56 countries for which anomaly returns are calculated.

2.4. Correlation overview of market state and sentiment indicators

In Table 2, we show pairwise correlations for the market state and sentiment indicators for the U.S. market (Panel A) and the other investigated countries ex U.S. (Panel B). In particular, the correlations between the *GOOD TIMES* (1), *UP* (2), *news sentiment (MP)* (3), and *investor sentiment (S)* (4) are interesting.

For measures (1) - (4), for both the U.S. market and international markets, there is a positive correlation significant at the 0.1% level with regard to the recession indicator. The correlation between *GOOD TIMES* and *UP* is 25%. This is to be expected, as the indicators are both based on stock market movements. In sum, all correlations from Panel B (Ex U.S.) of Table 2 are significant at the 0.1% level. For Panel A, and thus the correlations for the U.S. market, we observe similar correlations.

[9]We obtain the data from https://ec.europa.eu/.

[Table 2 about here.]

A direct comparison reveals notable differences, especially for the correlation of *GOOD TIMES* and *UP* with *news sentiment (MP)*. First, the correlation between *GOOD TIMES* and *news sentiment (MP)* is higher at 50% for the U.S. It seems that the relation between market states according to *GOOD TIMES* and news sentiment is stronger in the U.S.; however, the correlation between *UP* and *news sentiment (MP)* is slightly lower and the respective p-value is higher and is not significant at the 5% level. Moreover, the correlation of *news sentiment (MP)* with respect to the recalculated recession indicator is also slightly higher for the U.S.

Unexpected correlations can be seen for *investor sentiment (BW)*. Contrary to our expectation, the correlation between *GOOD TIMES* and *investor sentiment (BW)* is significantly negative, and the same applies for the correlation between *news sentiment (MP)* and *investor sentiment (BW)*. Since both sentiment indicators represent the emotional state of investors, the fact that they are negatively correlated is not obvious. On closer inspection, however, this may be due to the input information used to construct the sentiment variables. *News sentiment (MP)* is based on news and social media information, whereas *investor sentiment (BW)* relies on macroeconomic information.

3. Market states and cross-sectional anomaly returns

3.1. Methodology

Our initial data set consists of 250 anomalies. In the following analysis, we include only the anomalies with a significant abnormal performance alpha with respect to the Carhart (1997) four-factor model (FF4) based on a 5% level of significance ($|t| \geq 1.96$).[10] We chose the FF4 as our benchmark model given its prominence in the international asset pricing literature.

The methodology to determine the relation between anomalies and market states is based on a simple linear regression. Due to the aforementioned selection process, we control for the FF4 in order to take into account only the abnormal return that remains unexplained. We control for country fixed effects, since the regression is applied for different country groupings and thus several countries are included in the analysis. Furthermore, we consider monthly effects by clustering the standard deviation with respect to time t, since anomaly returns

[10]We conduct the selection process globally and provide the corresponding t-values for the anomalies in Table A.1 of the Internet Appendix. If the t-value of alpha is initially negative with regard to the FF4, the return of the respective anomaly is adjusted by the factor -1, such that all anomalies have a positive alpha.

across countries are not time independent. This gives us the ability to relax the assumption of independent observations and allows us to calculate correct standard deviations, although the monthly anomaly returns across countries are correlated. Formally, the regression model is as follows:

$$r_{i,t} = \alpha_i + \beta_{j,i} * MS_{j,t} + \sum_{n=1}^{4} \beta_{n,i} * r_{n,t} + f_{i,c} + \epsilon_{i,t} \tag{2}$$

In Equation 2, r corresponds to the return of anomaly i, n denotes a representative index for the four model factors of the FF4[11], and t denotes the time unit in months. $f_{i,c}$ denotes the country c fixed effect. MS is the placeholder for the respective market state or sentiment indicator j. Besides *GOOD TIMES* as main indicator, we make supplemental measurements with *UP*, *news sentiment (MP)*, and *investor sentiment (S)*, replacing MS in Equation 2. For the market state indicators, *GOOD TIMES* and *UP*, we use the indicator estimate for month t, which uses return data as of the end of month $t-1$. For the other indicators, we use the values from $t-1$ to take into account that no future information is incorporated, which is not available at time t.

We differentiate between market state indicators and sentiment indicators when assessing the results. The market state indicators are dummy variables. The results therefore represent the difference in anomaly returns between good and bad times. If we investigate the relation towards *GOOD TIMES* or *UP*, the intercept α_i corresponds to the performance in bad times. $(\alpha_i + \beta_{j,i})$ represents the performance in good times. The sentiment indicators are continuously measured variables and the regression parameter $\beta_{j,i}$ shows the return change for a change in sentiment of 1.[12]

3.2. Four-factor alphas of anomalies (value-weighted)

In our baseline measurement, we assess the relation between the unexplained value-weighted long-short portfolio return for different anomalies with regard to the Carhart (1997) asset pricing model (FF4) and the market state indicator *GOOD TIMES*.

[Table 3 about here.]

[11]If the anomaly i is already included within the FF4, the sum is adjusted accordingly and we do not control for this model factor on the right-hand side.

[12]Over all countries, we observe for *news sentiment (MP)* a mean of -0.053, a standard deviation of 0.213, a minimum of -1 and a maximum of 1. For standardized *investor sentiment (S)*, the mean is -0.001, the standard deviation is 1.006, the minimum is -3.193, and the maximum is 2.496.

Table 3 reports the corresponding results, measured across all 56 countries in our sample. Overall, out of the 138 investigated anomalies, 10 have a positive slope towards *GOOD TIMES*, significant at the 5% level. In contrast, for 51 anomalies the slope is negative and significant at the 5% level. The remaining 77 anomalies display no significant relation towards *GOOD TIMES*. The average abnormal return is 46.7 bps over all anomalies in bad times. In good times, the average abnormal return decreases by 15.5 bps to 31.2 bps. In relative terms, the abnormal returns are 49.8% higher in bad times.

If risk is the main driver for the existence of anomalies, we would expect that the majority of the anomalies have a higher abnormal return in good times according to consumption-based asset pricing theory. Since the results indicate on average a lower alpha in good times, this does not support the hypothesis for unmeasured risk. Rather, the results provide evidence towards mispricing with significant negative slopes for 37.0% of the anomalies. Nevertheless, 77 anomalies display no relation to *GOOD TIMES*. Hence, we cannot reject data-mining as a possible reason as to why so many anomalies were identified. However, our findings suggest that it is very unlikely to be the only reason.[13]

To see why data mining does not provide a good explanation for our findings, we generate a set of 1,000 random anomalies according to the description in Section 2.1 with significant performance regarding the Carhart (1997) four-factor model at the 5% level. For *GOOD TIMES*, Table 3 shows that 922 (92.2%) of fictitious anomalies are unrelated to the market states. For 78 of the generated anomalies, we observe a significant relation at the 5% level; 39 with better performance in good times, and 39 with better performance in bad times. First, the results do not have the same sensitivity to market states as the real published anomalies, where the slope of only 55.8% of the anomalies is insignificant. The 7.8% of random anomalies with a significant slope at the 5% level are Type-I error false discoveries. The actual percentage of false discoveries is above the expected percentage of 5%, which may be explained by fluctuations in the random sample and the fact that the return data are not normally distributed. Second,

[13] In addition, we measure equally-weighted long-short anomaly returns and examine their relation to *GOOD TIMES* in Table A.2 of the Internet Appendix. For this analysis, we exclude the 20 factors from asset pricing models like SMB, HML, etc., because they are defined as value-weighted portfolios in the research literature. Hence, the analysis for equally-weighted long-short returns relies on the remaining 118 anomalies with significant Carhart (1997) four-factor model alpha in their value-weighted version. The random generated anomalies are also equally-weighted. For *GOOD TIMES*, on average, there is an abnormal return of 52.4 bps in bad times and 35.7 bps in good times. In relative terms, this is an increase of 46.8%. In addition, for 53 (7) of 118 anomalies, the slope is negative (positive) at the 5% level of significance. In constrast, only 4.9% of random anomalies have a significant relation to *GOOD TIMES* at the 5% level.

for random anomalies that are significantly related to *GOOD TIMES*, the coefficient sign is as often positive as negative, whereas we observe for real anomalies a substantially higher percentage that have a significant negative relation to *GOOD TIMES*. This tendency is not present for randomly generated anomalies. In conclusion, there is no circumstantial evidence that data mining serves as the main reason for the existence of anomalies in general, even if for individual anomalies data mining might be a possible reason.

On a single anomaly view, there is arguably also some evidence supporting the risk-based explanation. For example, the model factors from Fama and French (1993) asset pricing model (FF3) show significant positive slopes for *GOOD TIMES* at least at the 1% level of significance. The market excess return MKTRF delivers an abnormal return of -5.3 bps in bad times. This increases in good times to 147.2 bps. The abnormal return for the size factor SMB is -32.2 bps in bad times and 39.1 bps in good times. Interestingly, for MKTRF and SMB, the abnormal returns are dominantly generated during good times, since the abnormal return in bad times is negative. The book-to-market ratio HML shows an alpha of 23.4 bps in bad times. In good times, this amounts to 70.6 bps. Hence, for the FF3 model factors, risk might serve as a reason for their existence.

To confirm our findings, in Table 3 we also provide the results for regressions that use *UP* as an alternative market state metric. The table also shows the results for regressions that explain abnormal anomaly returns with the sentiment indicators, *news sentiment (MP)* and *investor sentiment (S)*. For *UP*, we observe 30 (3) anomalies with a significantly negative (positive) slope. On average, the abnormal return for all anomalies increases between up- and down-markets by 14.6 bps from 32.9 bps to 47.5 bps and 44.5% in relative terms. This confirms our findings for *GOOD TIMES*. In particular, Cooper et al. (2004) investigate momentum and the relation towards market states according to *UP* for the U.S. market. We observe a higher performance for WML in up-markets of about 93.5 bps, significant at the 1% level. The return in up-markets (124.4 bps) decreases by 75.2% to 30.9 bps in down-markets. The same holds for *GOOD TIMES*, for which WML has a significantly higher alpha in good times, significant at the 0.1% level. In good times, there is an abnormal return of 137.3 bps; in bad times, the performance decreases by 79.2% to 28.5 bps. This is consistent with the findings from Cooper et al. (2004) for an international data set.

Similarly to market states, previous studies investigate investor sentiment with regard to anomaly returns (Stambaugh et al., 2012; Jacobs, 2015). Therefore, Table 3 also shows the results for regressions with *news sentiment (MP)* and *investor sentiment (S)* as independent variable instead of *GOOD TIMES*. As the sentiment variables are continuously measured, we restrict our attention to the direction of the relation without commenting on size effects. For *news sentiment (MP)*, we observe that 23 (7) anomalies have a lower (higher) abnormal return in periods of high news sentiment, significant at the 5% level. 108 anomalies show no significant relation with regard to news sentiment. For *investor sentiment (S)*, the sensitivity between anomaly return and sentiment is lower. Only 10 (2) anomalies display a lower (higher) performance in periods of high investor sentiment, significant at the 5% level, whereas 126 anomalies have no significant slope.

Our results for the relation of the investigated anomalies with regard to *news sentiment (MP)* and *investor sentiment (S)* are different from Stambaugh et al. (2012), who find that their set of anomalies is significantly stronger after periods of high investor sentiment. We therefore also examine the influence of the Baker and Wurgler (2006) sentiment measure (*investor sentiment (BW)*) on anomaly performance for the U.S. market. Table A.3 of the Internet Appendix provides the corresponding results. We observe, on average, a slope with regard to *investor sentiment (BW)* of 27.1 bps, which shows that in periods of high investor sentiment, the anomalies indeed perform better. With 98 insignificant anomalies and 37 (3) anomalies with higher (lower) performance after periods of high investor sentiment, the sensitivity towards *investor sentiment (BW)* is higher compared to *investor sentiment (S)*. Overall, these results are consistent with the findings of Stambaugh et al. (2012) and their hypothesis that if the anomalies reflect mispricing, the returns should be higher after periods of high investor sentiment.

The differences between the investor sentiment indicators show that the ability to predict the performance of anomalies is strongly dependent on the underlying sentiment proxy. This raises the interesting question, which of the three variables best measures or reflects investor sentiment. We do not intend to answer this question but instead conclude from the results that the various sentiment variables are conceptionally and empirically different from *GOOD TIMES*, and that viewed across all anomalies *GOOD TIMES* has a stronger influence on abnormal returns.

3.3. Raw anomaly returns and further control measurements

In Table 4, we conduct another analysis to confirm our previous finding. We examine the influence of *GOOD TIMES* on raw anomaly returns and on the alphas obtained from other asset pricing models, namely CAPM and FF6.[14] Again, we consider country fixed effects and cluster the standard deviations for the time steps t.

[Table 4 about here.]

For raw returns, we observe 59 (10) anomalies with a negative (positive) slope, significant at the 5% level, and only 69 anomalies show no significant relation towards *GOOD TIMES*. On average, the return for the anomalies is 49.7 bps (27.0 bps) in bad (good) times. Relatively, the return in bad times is 84.2% higher than in good times. We see similar findings if we inspect the CAPM and FF6 alphas. For the CAPM, 58 (14) anomalies tend to perform better in bad (good) times, significant at the 5% level; for FF6, there are still 47 (10) anomalies with higher (lower) unexplained returns in bad times. This is also reflected in the average performance for both market states. In bad times, we observe, on average, a performance of 49.8 bps (CAPM) and 39.8 bps (FF6), which reduces to 29.9 bps (CAPM) and 25.9 bps (FF6) in good times. In relative terms, the increase for bad times accounts to 66.8% and 53.4% for the CAPM alpha and FF6 alpha, respectively. The slightly lower sensitivity for FF6 - 81 anomalies have no significant relation to *GOOD TIMES* at the 5% level - can at least partly be explained by the fact that fewer anomalies have a significant overall alpha with regard to the FF6 model compared to the baseline FF4 model. Nevertheless, the results in Table 4 are similar to the ones with FF4 and support our conclusions.

3.4. Aggregated view on anomaly category and region

In Panel A of Table 5, we differentiate between six anomaly categories: *Model Factor*, i.e. the anomaly is used in an asset pricing model or is a central part of the related literature; *Market*, the anomaly incorporates information of market movements; *Fundamentals*, the anomaly is based on corporate data; *Valuation*, the anomaly measures price-to-value; *Analyst*, the anomaly deals with analyst assessments; and *Undefined*. We assign 16, 45, 51, 6, 9, and 7 anomalies to the categories. In addition, in Panel B of Table 5, we take a closer look at different regional affiliations (USA, Ex USA, DM, EM, and FM).

Each panel is separated into two parts. In the first columns, we provide the results for a panel regression using all available anomalies for the respective category or region. Since we incorporate the information for multiple anomalies, we additionally control for anomaly fixed

[14]The asset pricing model FF6 consists of the five model factors MKTRF, SMB, HML, CMA, and RMW from Fama and French (2015) and the momentum factor WML.

effects in the regression. We continue to investigate Carhart (1997) four-factor model alphas. Therefore, we exclude MKTRF, SMB, HML, and WML from the panel regression, because they are used as right-hand side variables in the regressions. For comparability, we also exclude the four factors from Carhart (1997) for the summarized individual results in the second part of each panel. All results are based on the relation to *GOOD TIMES*.

[Table 5 about here.]

In Panel A, all categories yield a higher abnormal return in bad times. All results are significant at the 5% level. The lower level of significance for the categories Valuation, Analyst, and Undefined is due to the significantly lower number of observations (N), owing to the smaller number of anomalies assigned to them. For market-based anomalies, we observe an abnormal return of 49.9 (29.4) bps in bad (good) times. This corresponds to an increase in bad times of 69.7%. Fundamental-based anomalies, perform 77.3% better in bad times than in good with an alpha of 40.6 (22.9) bps in bad (good) times. With an abnormal return of 80.1 (51.9) bps in bad (good) times, the relative increase for valuation-based anomalies accounts to 54.3%, and for analyst-based anomalies, we observe a relative increase of 68.6% in bad times related to 48.4 (28.7) bps in bad (good) times. For model factors and undefined anomalies, we observe similar results.

The individual results shown in the right part of Table 5 suggest that the anomalies with better performance in bad times gain more when there is a reversal of market states than anomalies with a better performance in good times. This is at first reflected by the fact that the number of anomalies with negative slopes, significant at the 5% level, is slightly higher than for significant positive slopes. Second, the negative average over all anomalies, shows for each category that the number of anomalies with a negative slope predominates the positive slopes without considering any significance level. Overall, only 34 anomalies exhibit a positive, while 100 exhibit a negative sign.

In Panel B, the available observations are categorized according to regions. The categories USA and Ex USA are obviously complementary to each other. This is also true for the MSCI categories DM, EM, and FM. For the panel regression of the USA (Ex USA), the slope is -35.4 bps (-19.0 bps), both significant at the 1% level. For both the USA and the rest of the world, we see that the anomalies tend to have higher abnormal returns in bad times than in good times. More precisely, for USA, the anomaly performance in bad (good) times is 65.3 bps (29.9 bps). For Ex USA, we observe an abnormal return of 47.8 bps (28.8 bps) in bad (good) times.

This corresponds to a relative increase for bad times of 118.4% for USA and 66.0% for Ex USA. The results again suggest that the anomalies tend to perform better in bad times than in good times. For both, USA and Ex USA, the number of negative slopes which are significant at the 5% level, is clearly higher than the number of positive and significant slopes. The bias towards bad times is more pronounced in Panel B than in Panel A, since all anomalies are included in each regional affiliation.[15] Furthermore, the return difference for anomalies with a higher performance in bad times is again higher compared to those with a higher performance in good times.

The MSCI categories exhibit similar results. For DM and EM the slopes for *GOOD TIMES* are significant at least at the 1% level. However, we do not find a significant effect of *GOOD TIMES* for the FM sample, which consists of fewer countries and substantially fewer anomaly-months than DM and EM.

To summarize, the aggregation of anomalies into categories, either based on anomaly definition or based on regional/market affiliation, confirms the implications from the individual anomaly view. Almost without exception, the anomalies for the categories tend to perform better in bad market states and have a higher abnormal return relative to good market states. This again suggests that anomalies often capture mispricing. Moreover, the category-wise view also serves to overcome the idiosyncratic nature of the individual view on anomalies. Thus, the consistency across anomaly categories suggests that the results are robust to the choice of selected anomalies.

3.5. Multivariate regression analysis

To assess whether the supplemental indicators *UP* and *news sentiment (MP)*[16] cover the same information or add additional explanatory power with regard to the predictability of the Carhart (1997) four-factor model alpha compared to *GOOD TIMES*, we repeat the analysis from Subsection 3.4 on a multivariate basis. In addition to *GOOD TIMES*, we include one of the mentioned indicators as an independent variable.

[Table 6 about here.]

[15] For FM, the individual results for anomaly rd_inc, unexpected R&D increases (Eberhart et al., 2004) are not included due to missing information.

[16] *Investor sentiment (S)* is not included, since the previous results show that the anomaly performance is not significantly dependent on this indicator and especially for the regional aggregation, the coverage is small. The results by anomaly category are in Table A.4 of the Internet Appendix.

For the results by anomaly category in Panel A, adding *UP* to the regression leads as expected to a small decrease for $|\beta_{GOOD}|$ as compared to Table 5 for almost all categories. This indicates that *UP* offers a small amount of explanatory power and is also reflected by the fact that overall, the slopes for both *GOOD TIMES* and *UP* are significant at least at the 1% level. However, in anomaly categories, we only observe a significant slope for *UP* for the model factors and the fundamental-based anomalies, whereas *GOOD TIMES* continuous to be a significant predictor across all categories. Overall, the evidence is in line with our results from Table 1, in which *GOOD TIMES* and *UP* are already similar, and it also corresponds to the findings of Table 3, in which we observe a lower sensitivity to *UP* than to *GOOD TIMES*. Overall, the fact that all slopes from the panel regression are negative for *UP* and *GOOD TIMES*, without taking into account the significance level, is in line with the notion that most anomalies perform better in bad market states, irrespective of which market state proxy is used.

When adding *news sentiment (MP)* to the regression of *GOOD TIMES*, we observe no significant results for β_{GOOD} for the model factors or the undefined anomalies. This might be due to the lower number of observations for *news sentiment (MP)* compared to *UP*. However, we find a significant slope for *news sentiment (MP)* at the 5% level for all categories except for the fundamental- and valuation-based anomalies. In conclusion, *news sentiment (MP)* provides a small amount of additional information and the insignificant results for β_{GOOD} for two categories are due to adding *news sentiment (MP)*. Nevertheless, across all anomalies, *GOOD TIMES* continues to be statistically significant at the 0.1% level after accounting for *news sentiment (MP)*.

When distinguishing between different regional affiliations (Panel B), the results for β_{GOOD} remain quite similar after adding *UP*. In addition, the individual results confirm our impression that *UP* does not provide a substantial amount of further information. The number of significant slopes are higher for *GOOD TIMES* for both market state indicators for all regions except FM.

For *news sentiment (MP)*, we find that for the U.S. market, the slopes for both indicators are not significant. However, the absolute value for $\beta_{Control}$ is higher compared to the other regions. This explains, why $\beta_{Control}$ becomes insignificant. In addition, the intercept α is now significant at the 5% level, not the 0.1% level as before. Although, the values are comparable to the results from Table 5, there are highly different p-values for the regression parameter in the U.S. market after adding *news sentiment (MP)*. This leads to the assumption that *news* *sentiment (MP)* plays a role for investors in the U.S. market.

4. Robustness Tests

4.1. Analysis of the long- and short side of anomalies

Following Stambaugh et al. (2012), we investigate the long and short side of anomalies separately with regard to market states. We build the long and short side of the Carhart (1997) four-factor model alpha as excess return over the risk-free rate. Due to limits-to-arbitrage and the unwillingness of investors to short, mispricing is more pronounced on the short side. To the extent anomalies reflect mispricing, we therefore expect that the long side is not greatly affected by *GOOD TIMES*. In contrast, the observed relation for the long-short anomalies should be driven by the short side.

[Table 7 about here.]

In Panel A of Table 7, we observe for the long side that only model factors, market-based anomalies, and the anomalies without specific categorization have a significant relation to *GOOD TIMES* at the 1% level. The slopes with regard to *GOOD TIMES* are not significant at the 5% level for the other categories. In contrast, the abnormal return of the short side always displays an economically substantial and statistically significant relation to *GOOD TIMES*. For fundamental-based anomalies, the abnormal return is -35.5 bps in bad times and -15.5 bps in good times, which is an increase in profitability of 129.0% in bad times. We observe the short side has the smallest increase in profitability for market-based anomalies, which delivers an abnormal return of -40.6 bps in bad times and -32.0 bps in good times (26.9%). The other categories exhibit similar results. This confirms our expectation that the long side is not strongly influenced by the market states across the anomalies and that the short side is more profitable in bad times.

In Panel B, for U.S. and Ex U.S., the long side of the anomalies is not significant. The MSCI categories show that the relation for DM and FM is significant at the 5% level. For EM, the long side does not have a significant reaction to *GOOD TIMES*. In addition, the short side exhibits a positive slope for all regional affiliations, significant at the 1% level. In sum, the results confirm our hypothesis with regard to the short side, but the long side is for some regional affiliations statistically dependent on *GOOD TIMES*. Thus, we observe that in bad times the short side is at least twice as profitable as the long side. In addition, the slope to

GOOD TIMES is significantly higher for the short side. For example, for DM, the relation to *GOOD TIMES* is 1.5 times higher on the short side, although the slope of the long side is statistically significant.

The only exception is FM, where in general small, risky, and mostly illiquid markets are included. For FM, we observe a higher slope on the long side. In these markets, special rules prevail and due to their small market capitalization, they cannot be considered as the sole representative of the global financial market. Nevertheless, it is interesting to consider. Thus, our hypotheses, especially for the long side, do not hold for FM. Both the long side and the short side show a significantly higher return in good market states. This also confirms the finding from Table 5, where we do not observe a significant relation across the long-short anomalies with respect to the *GOOD TIMES*.

Overall, for 137 long-short anomalies[17], we find an abnormal return of 47.0 bps in bad times and 30.4 bps in good times. This corresponds to an average increase of 16.6 bps across the anomalies in bad times. For the long side, we observe a performance of 10.2 bps in bad times and 9.6 bps in good times, and for the short side, a performance of -36.3 bps in bad times and -21.2 bps in good times. Therefore, the long side increases by 0.6 bps and the short side is 15.1 bps more profitable in bad times. Hence, the contribution for the relation to *GOOD TIMES* is separated into 96.6% (3.4%) for the short (long) side. Taking this into account, the short side is more strongly related to market states than the long side. The observed asymmetry between the long and short side is most consistent with a mispricing-based explanation of higher abnormal returns for the anomalies in bad market states.

5. Conclusion

In the past decades, a large number of anomalies have been discovered, which gave rise to the "zoo of anomalies" (Cochrane, 2011). To better understand the origin of anomalies, we analyze the abnormal returns of 118 anomalies and 20 known model factors across market states for a global stock data set. We formulate different expectations about the performance of anomalies across market states according to the three prevalent explanations for anomalies: risk, mispricing, and data-mining.

Our results indicate that many of the anomalies we consider have significantly higher abnormal returns in bad market states than in good market states. This assessment is robust

[17] We exclude MKTRF for this comparison, since this is not calculated as a classical long-short portfolio.

across different anomaly classifications and regions, and it persists if we additionally control for investor sentiment. We also find that the relation to market states is mostly driven by the short side.

We argue that our findings are inconsistent with the idea that all anomalous return patterns can be explained by data-mining or risk. In contrast, underreaction-based mispricing coupled with limits-to-arbitrage provides the best explanation of why many anomalies perform better in bad times and on the short side. Therefore, we conclude that a large fraction of anomalies are indeed real, which suggests a violation of the efficient market hypothesis for global equity markets. We emphasize that this assessment is a based on a broad picture view, which does not exclude risk or data-mining as possible explanations for (many) individual anomalies.

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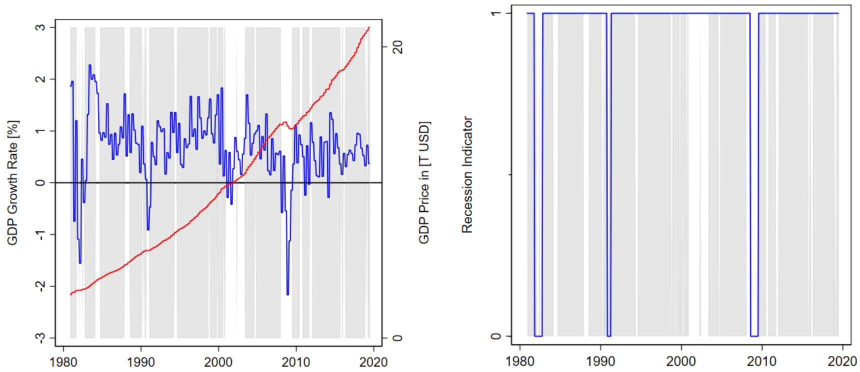
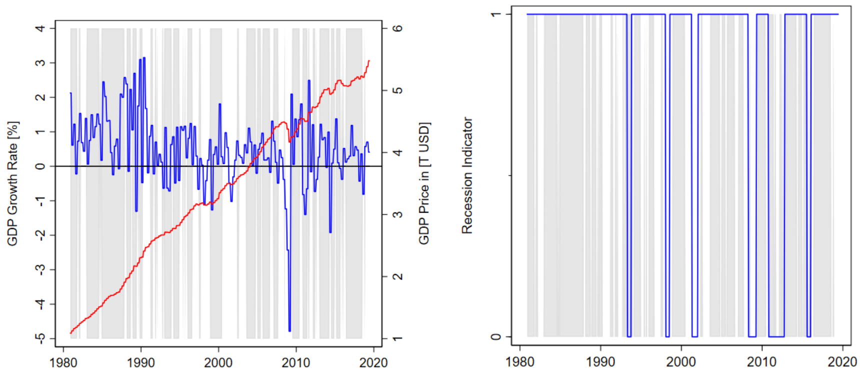
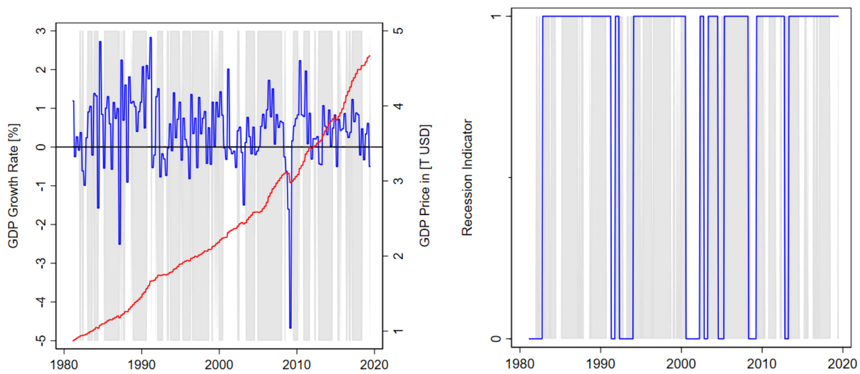
Figure 1: **Good times indicator illustration**
This figure illustrates GOOD TIMES for the G7 countries. The shading indicates good times and white stands for bad times. The left subfigure gives reference to GDP growth (blue) and the GDP level (red). The right subfigure displays the definition of recessions.



(a) USA



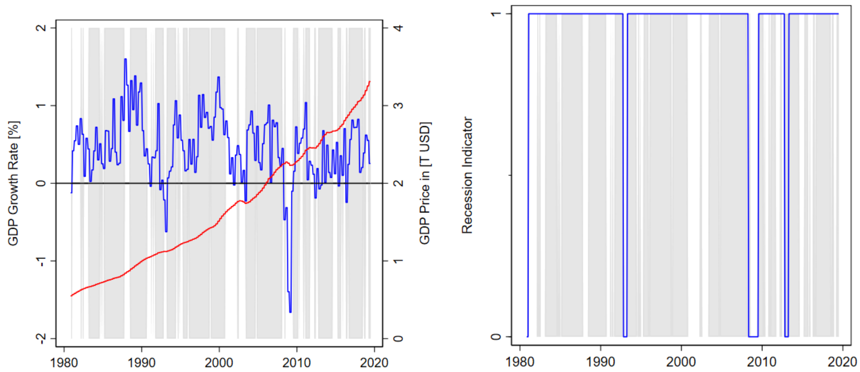
(b) Japan



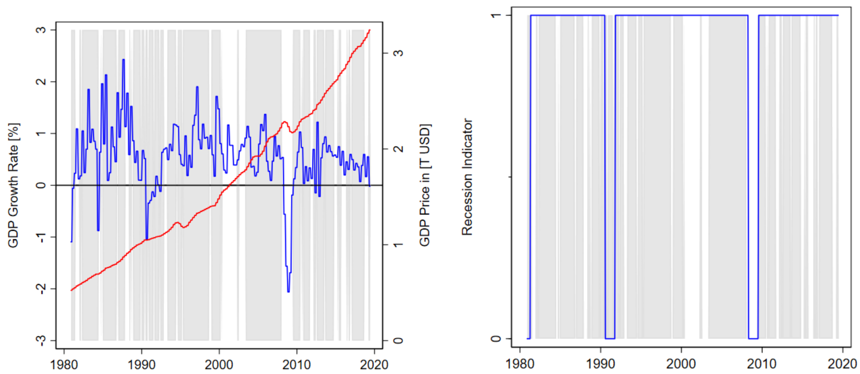
(c) Germany

[Continued on next page]

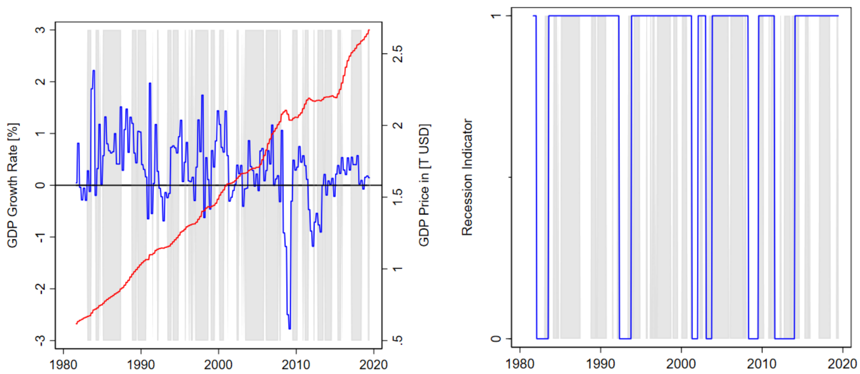
Figure 1: **(continued)**



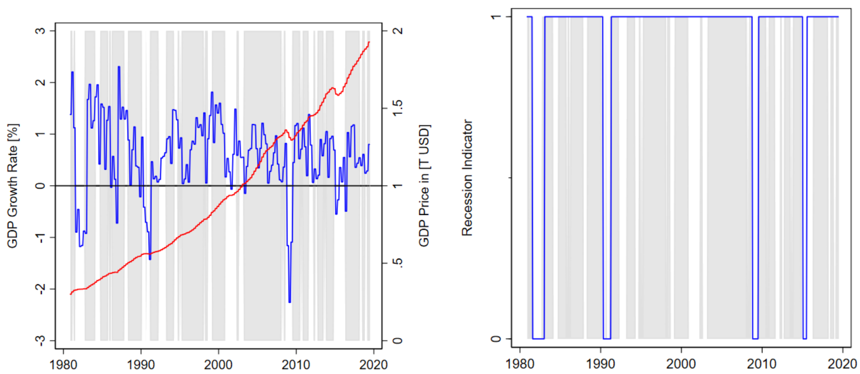
(d) France



(e) United Kingdom



(f) Italy



(g) Canada

Table 1: **Indicator overview**

This table gives an overview of GOOD TIMES and UP for the U.S. market (Panel A) and OECD countries except the U.S. (Panel B). In this table, we investigate a time series from September 1981 to June 2019. In addition, we compare the indicators with the definition of recessions. (1.) shows the amount of months indicated as good or bad time for each indicator. (2.) displays the percentage of equivalent market state assignments of GOOD TIMES and UP with respect to the recession indicator. For Panel B, the results represent the averages over all considered countries.

Panel A: Good Times U.S.

(1.) Number (Percentage) of Months by Good and Bad Times

	GOOD TIMES	UP	Recession Ind.
# Good Times	360 (77.586%)	370 (86.247%)	435 (93.548%)
# Bad Times	104 (22.414%)	59 (13.753%)	30 (6.452%)

(2.) Percentage of Equivalence

		GOOD TIMES	UP
Recession Ind.	Good Times	81.336%	87.591%
	Bad Times	76.667%	44.444%
	Overall	81.034%	85.781%

Panel B: Good Times OECD Countries except U.S.

(1.) Percentage of Months by Good and Bad Times

	GOOD TIMES	UP	Recession Ind.
# Good Times	64.510%	71.953%	85.969%
# Bad Times	35.490%	28.047%	14.031%

(2.) Percentage of Equivalence

		GOOD TIMES	UP
Recession Ind.	Good Times	63.073%	52.273%
	Bad Times	68.546%	75.570%
	Overall	67.520%	72.839%

Table 2: **Correlation of different market state/sentiment indicators**
This table shows the correlation matrices for different market state and sentiment indicators. These are the GOOD TIMES (1), UP (2), news sentiment (MP) (3), investor sentiment (S) (4), the indicator calculated based on the definition of recessions (5) and GDP growth (6). For the U.S. market, we added investor sentiment (BW) (7). We mainly used information from September 1981 until June 2019. The MarketPsych indicator is only available from December 1997. In addition, some indicators are not available for every country. For example, the GDP growth and the the recession indicator are only used for OECD countries. Panel A displays the correlation for USA and Panel B shows the correlation for the other countries except the U.S.

Panel A: Correlation Matrix U.S.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) GOOD TIMES	1	0.263***	0.500***	0.217***	0.342***	0.282***	−0.189***
(2) UP		1	0.093	0.318***	0.186***	0.156***	0.346***
(3) News Sentiment (MP)			1	0.222***	0.286***	0.434***	−0.216***
(4) Investor Sentiment (S)				1	0.497***	0.423***	0.251***
(5) Recession Ind.					1	0.579***	0.094*
(6) GDP Growth						1	0.058
(7) Investor Sentiment (BW) U.S.							1

Panel B: Correlation Matrix except U.S.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) GOOD TIMES	1	0.256***	0.185***	0.111***	0.205***	0.168***
(2) UP		1	0.117***	0.238***	0.222***	0.169***
(3) News Sentiment (MP)			1	0.160***	0.148***	0.140***
(4) Investor Sentiment (S)				1	0.432***	0.330***
(5) Recession Ind.					1	0.488***
(6) GDP Growth						1

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3: **Regression analysis by good and bad times (value-weighted)**
This table displays the results of the Carhart (1997) four-factor model (FF4) alpha for 138 anomalies i, calculated with value-weighted portfolios (5. quintile - 1. quintile), in relation to GOOD TIMES and further market state/sentiment indicators (MS). We follow the methodology:

$$r_{i,t} = \alpha_i + \beta_{j,i} * MS_{j,t} + \sum_{n=1}^{4} \beta_{n,i} * r_{n,t} + f_{i,c} + \epsilon_{i,t}$$

If the tested anomaly i is part of the FF4, the respective control variable is excluded. Since we incorporate 56 countries (international), we control for country effects $f_{i,c}$. The standard errors are clustered with regard to time t. The first column represents the anomaly category, the second column is the anomaly acronym, the third (fourth) column stands for the intercept (slope) of the regression with regard to GOOD TIMES, the fifth to seventh column are the slopes for UP, news sentiment (MP), and investor sentiment (S), respectively. The sample covers monthly anomaly returns from September 1981 until June 2019. The summary statistics # Sign. β correspond to the 5% level.

		GOOD TIMES		UP	News Sentiment (MP)	Investor Sentiment (S)
Category	Anomaly	α	β	β	β	β
FF3	MKTRF	−0.053	1.419**	−0.39	11.172***	0.027
	SMB	−0.322***	0.713***	−0.042	1.169***	0
	HML	0.234*	0.472***	−0.092	0.725*	0.094
FF5	RMW	0.595***	−0.174	−0.172	−0.113	−0.072
	CMA	0.262**	−0.272**	−0.204	−0.057	0.025
DHS3	FINAN	0.660***	−0.281**	−0.212*	−1.153*	−0.018
	EAR6M	0.383***	0.388***	−0.026	−0.245	0.052
SY4	MGMT	0.605***	−0.152	−0.227	−0.586	−0.069
	PERF	0.458**	0.069	−0.063	−0.795	−0.08
q5	ME	−0.057	0.125	0.123	0.451*	−0.012
	IA	0.475***	−0.304*	−0.295*	−0.055	−0.006
	ROE	0.914***	−0.009	−0.307*	−0.54	0.047
	EIGM	0.459***	−0.094	−0.181*	−0.376	−0.047
Carhart	WML	0.285	1.088***	0.935**	1.238*	0.409*
Other model factors	EIGA	0.361***	−0.019	−0.196*	−0.6	−0.064
	HMLm	0.692***	−0.289**	−0.065	−0.289	−0.036
	RMW_A	0.566***	−0.205	−0.288*	−0.694	−0.119
	RMWc	0.518***	−0.14	−0.262*	−0.790*	0.013
	ROE_qu	0.705***	0.095	−0.038	−0.837	0.023
	STR	0.611**	−0.781***	−0.275	−0.715	0.019
Market	atr	0.799***	−0.390**	−0.164	−0.772	−0.074
	trad_vol_60m	0.231**	−0.515***	−0.411**	−0.551	−0.129
	avol3d	0.526***	−0.138	−0.355*	−0.093	−0.073
	b1f_res_1m	0.936***	−0.517*	−0.239	−0.985	−0.096
	b1f_res_60m	0.900***	−0.552**	−0.159	−1.761***	0.139
	beta_unc_all	0.065	0.195	0.276	0.808	0.028
	chmom	0.467*	−0.434*	−0.356	−1.042*	−0.118
	com_eq	0.660***	−0.224	−0.334*	−0.78	−0.088
	corwin0	0.663***	−0.26	−0.216	−1.059	0.024
	d_loser	0.483**	0.03	0.056	−0.556	−0.025
	d_rsplit6m	1.492***	−0.114	−0.523	−2.983	−0.076
	d_seo_3yr	−0.177**	0.099	0.084	−0.165	0.162**
	d_shock_neg	0.677**	0.083	−0.216	−1.143	0.089
	d_shock_pos	1.457***	−1.158***	−0.395	−0.911	−0.182
	d_winner	0.819***	−0.442**	−0.127	−0.703	−0.142
	ear3d	0.2	0.485***	−0.016	−0.019	−0.006

		GOOD TIMES		UP	News Sentiment (MP)	Investor Sentiment (S)
Category	Anomaly	α	β	β	β	β
Market	fric	−0.13	0.12	0.062	−0.107	−0.023
	iltr_5y_vw	0.009	0.335	−0.004	0.831	0.078
	imom_2_6_vw	−0.231	0.041	0.078	0.165	−0.037
	iret_scm_vw	0.609***	−0.327**	−0.178	−0.008	−0.016
	irev_13_18_vw	0.346	−0.38	−0.032	−0.552	−0.04
	irev_1m_vw	0.591**	0.172	−0.054	−0.266	−0.012
	iskew_kumar	0.272**	−0.290*	−0.026	−0.122	−0.035
	iu	0.294*	0.186	0.005	−0.017	0.067
	ivol_kumar	0.894***	−0.482*	−0.216	−1.934**	−0.107
	kurt_1f_60m	0.427***	−0.235	0.033	−0.265	0.121
	lotterystock	0.598***	−0.376*	0.162	−0.15	0.105
	max_ret_daily	0.455*	−0.204	−0.122	−0.49	−0.087
	min_ret_daily	−0.013	0.393*	0.037	−0.257	0.038
	mom_2_6	−0.302	0.546**	0.264	1.257**	0.113
	mom_7_12	0.451**	−0.233	−0.212	−0.463	−0.207*
	r21f_60m	0.757***	−0.672***	−0.431***	−1.082**	−0.085
	ret_Comp	0.672**	0.01	0.024	−0.73	−0.055
	ret_scm	0.746***	−0.290*	−0.072	0.142	−0.073
	ret_smofq1y	0.209	0.191	−0.203	0.728	−0.049
	sesm	1.017**	−0.104	−0.426	−0.224	−0.246
	sesm_scm	0.628***	−0.07	−0.159	−0.536	−0.317*
	turn_3m	0.637***	−0.505***	−0.293*	−0.119	−0.144
	size	0.057	0.349***	0.233*	0.067	0.11
	skew_1f_60m	0.659***	−0.352*	−0.039	−0.289	0.074
	std_dolvol	0.246**	−0.610***	−0.415***	−0.515	−0.156
	trendfactor	1.026***	−0.790***	−0.357	−0.882	−0.062
	trendfactor_cheap	0.411**	−0.356*	0.058	−0.263	−0.101
	vol_mcap	0.642***	−0.683***	−0.27	−0.248	−0.201
	zero	0.995***	−0.721***	−0.459*	−0.627	−0.183
Valuation	cf_mcap_mo	1.272***	−0.467*	−0.364	−0.715	−0.165
	cfp_ia_mo	1.012***	−0.404**	−0.329*	−0.683	−0.238*
	ipo_rd	0.299**	−0.292*	0.003	−1.134**	0.02
	nit_mcap_mo	1.088***	−0.429*	−0.254	−0.823	−0.105
	rsup1	0.183	0.143	−0.059	0.714	−0.136
	sprc_mo	0.803***	−0.178	−0.235	−0.521	−0.182

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Table 3: **(continued)**

Category	Anomaly	GOOD TIMES α	GOOD TIMES β	UP β	News Sentiment (MP) β	Investor Sentiment (S) β
Fundamentals	a_turn	0.503***	−0.144	−0.237	−0.159	−0.164*
	acc_slo	0.371*	−0.063	−0.261	−0.303	0.04
	acfo	0.556***	−0.343**	−0.275	−0.54	−0.149
	ag	0.312*	−0.409**	−0.107	0.01	0.104
	aprodc	0.185	0.037	−0.105	−0.122	−0.034
	cash	0.189	0.005	−0.226	0.229	−0.251**
	cashdebt	0.903***	−0.449**	−0.29	−1.045*	−0.178
	cdind	0.227	−0.125	−0.323*	−0.487	−0.08
	cf_var_mo	0.171	−0.221	0.153	−0.658	0.131
	ch_fc_acc	0.435***	−0.066	−0.221	−0.278	−0.06
	cto	0.178	0.022	−0.164	0.406	−0.342**
	d2a	0.321	−0.059	−0.33	0.208	−0.117
	del_cash1	0.153	−0.03	−0.075	−0.43	−0.055
	diss	0.195**	−0.158*	−0.149	−0.144	−0.003
	dist_e	0.658***	−0.401**	−0.344*	−0.936*	−0.023
	dpfs	0.271	−0.339*	−0.239	−0.849*	−0.132
	dur	0.519***	−0.174	−0.129	−0.198	−0.099
	dXFIN1	0.609***	−0.398**	−0.347**	−0.853*	−0.065
	dXFIN2	0.705***	−0.549***	−0.278*	−0.885*	−0.044
	e_cons	0.284*	−0.193	−0.2	−0.807*	−0.01
	earn_per	0.259*	−0.169	−0.094	−0.641	−0.027
	earn_pred	0.709***	−0.392**	−0.192	−0.467	−0.174
	gp	0.752***	−0.318*	−0.213	−0.319	−0.138
	ia	0.267*	−0.205	−0.01	0.58	0.057
	laborprod_ia	0.233*	−0.240*	−0.102	−0.564	0.008
	lag_ag	−0.052	0.043	0.16	0.164	0.061
	ltprofit	0.659***	−0.412**	−0.181	−0.317	0.012
	margin	0.408***	−0.225	−0.037	0.11	−0.029
	nincr_up	0.316*	0.194	0.112	0.112	−0.059
	noa_lev	0.492***	−0.336**	−0.228	−0.432	−0.135
	nop_mo	0.927***	−0.543***	−0.439**	−1.279**	−0.086
	ns	0.172	−0.051	0.132	0.256	0.075
	ns_ti	0.154	0.025	−0.057	−0.728	−0.016
	nwc_chng	0.480***	−0.27	−0.269	−0.312	−0.02

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Category	Anomaly	GOOD TIMES α	GOOD TIMES β	UP β	News Sentiment (MP) β	Investor Sentiment (S) β
Fundamentals	op_ff	0.804***	−0.356*	−0.317	−0.971	−0.12
	org_cap	0.248*	−0.155	−0.295*	−0.168	−0.276***
	pchcurrat	0.014	−0.018	0.024	−0.063	0.015
	pm	0.496**	−0.173	−0.289	−1.162*	−0.053
	rd_inc	−0.187	0.267	0.513	3.354*	−0.315
	rna	0.665***	−0.183	−0.156	−0.79	−0.171
	roaq	0.981***	−0.159	−0.213	−1.454**	0.068
	roe_2	0.684***	−0.234	−0.061	−0.993*	−0.067
	roic	0.952***	−0.438**	−0.36	−1.035*	−0.142
	rsup2	0.354**	−0.032	−0.292	−0.147	−0.055
	sga_at	0.151	0.022	−0.361*	0.361	−0.196*
	std_emp	0.345*	−0.228	−0.392*	0.523	−0.303**
	sue	0.453**	0.132	0.049	0.471	−0.03
	tang	0.201	−0.047	−0.412**	0.528	−0.107
	tang2	0.254*	−0.088	−0.18	0.363	−0.164
	tax1	0.291**	−0.177	−0.299*	−0.258	−0.139
	usd_exp	0.171	0.071	0.329	1.008	0.03
Analyst	an_value	1.009***	−0.541**	−0.454*	−1.743**	−0.07
	chnanalyst	−0.13	0.094	0.115	−0.314	0.183
	del_ltg	0.265*	−0.035	−0.066	−0.493	0.014
	down_f	0.096	0.197*	0.211*	0.452	0.082
	efp	1.081***	−0.628**	−0.602**	−2.039**	−0.074
	eps_disp	0.677***	−0.337	0.293	−0.448	−0.147
	ltg	0.528***	−0.419*	−0.185	−1.039*	−0.059
	re_1	0.297*	0.096	0.149	0.307	0.124
	up	0.186*	0.001	−0.054	0.156	0.022
Undefined	failure	0.495**	−0.134	−0.06	−0.968	−0.001
	kz	0.774***	−0.487***	−0.380**	−1.111**	−0.127
	oscore	0.808***	−0.542***	−0.487**	−1.320**	−0.154
	qmj	0.503***	−0.254*	−0.21	−0.011	−0.121
	shum	0.497***	−0.183	−0.11	−0.454	−0.089
	sin	0.314*	−0.144	−0.12	0.369	0.016
	zscore	0.412**	−0.162	−0.337*	−0.812	−0.248**
	Average	0.467	−0.155	−0.146	−0.272	−0.054
	Summary	# Sign. β (> 0)	10	3	7	2
		# Sign. β (< 0)	51	30	23	10
		# Non-sign. β	77	105	108	126
	Random anomalies	# Sign. β (> 0)	39	27	33	18
		# Sign. β (< 0)	39	21	30	39
		# Non-sign. β	922	952	937	943

Table 4: **Regression analysis - Raw returns and other control models**

This table displays the results of the raw anomaly returns, CAPM-, and six-factor model (FF6) alpha for 138 anomalies i, calculated with value-weighted portfolios (5. quintile - 1. quintile), in relation to GOOD TIMES. We follow the methodology:

$$\text{Raw}: \quad r_{i,t} = \alpha_i + \beta_{GOOD,i} * MS_{GOOD,t} + f_{i,c} + \epsilon_{i,t}$$

$$\text{CAPM}: \quad r_{i,t} = \alpha_i + \beta_{GOOD,i} * MS_{GOOD,t} + \beta_{MKTRF,i} * r_{MKTRF,t} + f_{i,c} + \epsilon_{i,t}$$

$$\text{FF6}: \quad r_{i,t} = \alpha_i + \beta_{GOOD,i} * MS_{GOOD,t} + \sum_{n=1}^{6} \beta_{n,i} * r_{n,t} + f_{i,c} + \epsilon_{i,t}$$

If the tested anomaly i is part of the FF4, the respective control variable is excluded. Since we incorporate 56 countries (international), we control for country effects $f_{i,c}$. The standard errors are clustered with regard to time t. The first column represents the anomaly category, the second column is the anomaly acronym, the third (fourth) column stands for the intercept (slope) of the regression with regard to GOOD TIMES, the fifth to seventh column are the slopes for UP, news sentiment (MP), and investor sentiment (S), respectively. The sample covers monthly anomaly returns from September 1981 until June 2019. The summary statistics # Sign. β correspond to the 5% level.

		Raw Return		CAPM		FF6	
Category	Anomaly	α	β	α	β	α	β
FF3	MKTRF	−0.004	1.051*	−0.004	1.051*	0.187	1.240**
	SMB	−0.391***	0.548***	−0.378***	0.678***	−0.227**	0.694***
	HML	0.339**	0.226	0.335**	0.191	0.304**	0.413**
FF5	RMW	0.611***	−0.346**	0.615***	−0.265*	0.593***	−0.159
	CMA	0.327**	−0.291*	0.329**	−0.225	0.266**	−0.241*
DHS3	FINAN	0.667***	−0.369**	0.669***	−0.282*	0.563***	−0.267*
	EAR6M	0.466***	0.392**	0.466***	0.434***	0.380***	0.369***
SY4	MGMT	0.630***	−0.256	0.631***	−0.161	0.439***	−0.008
	PERF	0.562	0.279	0.564*	0.526*	0.375**	0.014
q5	ME	−0.2	0.595***	−0.196	0.730***	−0.066	0.116
	IA	0.444**	−0.224	0.447***	−0.148	0.226**	−0.028
	ROE	1.030***	−0.052	1.034***	0.032	0.844***	−0.068
	EIGM	0.459***	−0.2	0.470***	−0.133	0.325***	−0.102
Carhart	WML	0.253	0.830*	0.251	1.031***	0.189	1.114***
Other model factors	EIGA	0.391***	−0.138	0.400***	−0.065	0.200*	0.006
	HMLm	0.757***	−0.317	0.745***	−0.420*	0.725***	−0.310**
	RMW_A	0.587***	−0.383**	0.594***	−0.296*	0.371***	−0.228*
	RMWc	0.587***	−0.310*	0.588***	−0.204	0.195**	−0.008
	ROE_qu	0.940***	−0.014	0.939***	0.085	0.629***	0.005
	STR	0.611**	−0.879***	0.609**	−0.967***	0.685**	−0.830***
Market	atr	0.866***	−0.337**	0.866***	−0.370**	0.741***	−0.341*
	trad_vol_60m	0.468*	−0.717**	0.462***	−1.128***	0.245**	−0.531***
	avol3d	0.559***	−0.128	0.557***	−0.228	0.433***	−0.05
	b1f_res_1m	0.981***	−0.784**	0.984***	−0.690**	0.742***	−0.396*
	b1f_res_60m	0.943***	−0.801***	0.944***	−0.790***	0.679***	−0.455*
	beta_unc_all	0.151	−0.057	0.148	−0.079	0.079	0.141
	chmom	0.441*	−0.766**	0.439*	−0.862***	0.511*	−0.489*
	com_eq	0.705***	−0.27	0.719***	−0.126	0.557***	−0.212
	corwin0	0.874***	−0.656**	0.873***	−0.506*	0.551**	−0.229
	d_loser	0.487*	0.021	0.487*	0.032	0.397*	0.053
	d_rsplit6m	1.880***	−0.715	1.891***	−0.679	1.472***	−0.161
	d_seo_3yr	−0.186*	0.206	−0.188**	0.094	−0.074	0.034
	d_shock_neg	0.497*	0.146	0.497*	0.128	0.545*	0.189
	d_shock_pos	1.577***	−1.244***	1.577***	−1.256***	1.290***	−1.062***
	d_winner	0.770***	−0.513**	0.771***	−0.475**	0.724***	−0.431**
	ear3d	0.429***	0.344*	0.430***	0.380**	0.195	0.486***

		Raw Return		CAPM		FF6	
Category	Anomaly	α	β	α	β	α	β
Market	fric	−0.11	0.137	−0.109	0.16	−0.093	0.112
	iltr_5y_vw	0.028	0.255	0.027	0.219	0.072	0.29
	imom_2_6_vw	−0.303	−0.284	−0.304	−0.351	−0.146	−0.06
	iret_scm_vw	0.501***	−0.351**	0.502***	−0.341**	0.618***	−0.369**
	irev_13_18_vw	0.226	−0.338	0.226	−0.345	0.378	−0.385
	irev_1m_vw	0.506**	0.235	0.506**	0.275	0.540**	0.19
	iskew_kumar	0.401***	−0.608***	0.400***	−0.648***	0.254*	−0.271*
	iu	0.324	−0.175	0.333*	0.204	0.091	0.273
	ivol_kumar	1.005***	−0.822**	1.008***	−0.714**	0.654**	−0.318
	kurt_1f_60m	0.438***	−0.310*	0.435***	−0.366**	0.370***	−0.258*
	lotterystock	0.869***	−0.897***	0.876***	−0.784***	0.472***	−0.349*
	max_ret_daily	0.387	−0.341	0.393*	−0.021	0.314	−0.135
	min_ret_daily	−0.105	0.369	−0.104	0.698**	−0.151	0.472*
	mom_2_6	−0.034	1.221***	−0.03	1.404***	−0.295	0.535**
	mom_7_12	0.656**	0.158	0.658***	0.225	0.507**	−0.338
	r21f_60m	0.938***	−0.946***	0.914***	−1.329***	0.672***	−0.605***
	ret_Comp	0.620**	0.049	0.621***	0.081	0.612**	0.068
	ret_scm	0.654***	−0.289*	0.653***	−0.330**	0.791***	−0.375**
	ret_smofq1y	0.425	0.619*	0.426	0.687**	0.206	0.166
	sesm	1.005***	0.015	1.000***	0.14	0.944**	−0.033
	sesm_scm	0.516**	0.243	0.521***	0.331*	0.575**	−0.035
	turn_3m	0.737***	−0.413*	0.732***	−0.735***	0.671***	−0.561***
	size	−0.204	0.735***	−0.2	0.962***	0.11	0.352***
	skew_1f_60m	0.675***	−0.589***	0.671***	−0.661***	0.629***	−0.373**
	std_dolvol	0.444*	−0.746**	0.438***	−1.155***	0.236*	−0.603***
	trendfactor	0.921***	−0.822***	0.917***	−0.898***	1.000***	−0.725***
	trendfactor_cheap	0.337*	−0.335*	0.335*	−0.397*	0.385**	−0.341*
	vol_mcap	0.709**	−0.325	0.702***	−0.770***	0.724***	−0.757***
	zero	1.028***	−0.591*	1.072***	−1.073***	0.995***	−0.748***
Valuation	cf_mcap_mo	1.397***	−0.769***	1.397***	−0.785***	1.037***	−0.484**
	cfp_ia_mo	0.909***	−0.291	0.908***	−0.370*	0.948***	−0.435**
	ipo_rd	0.455***	−0.450***	0.453***	−0.525***	0.19	−0.249*
	nit_mcap_mo	1.178***	−0.667**	1.177***	−0.680**	0.963***	−0.465*
	rsup1	0.365**	0.146	0.366**	0.161	0.223	0.026
	sprc_mo	0.685***	0.001	0.684***	−0.023	0.705***	−0.188

[Continued on next page]

Table 4: **(continued)**

Category	Anomaly	Raw Return α	Raw Return β	CAPM α	CAPM β	FF6 α	FF6 β
Fundamentals	a_turn	0.494***	−0.219	0.495***	−0.139	0.348***	−0.076
	acc_slo	0.555***	−0.295	0.556***	−0.278	0.304*	0.015
	acfo	0.720***	−0.616***	0.722***	−0.578***	0.413***	−0.315*
	ag	0.370*	−0.393*	0.373**	−0.322*	0.111	−0.155
	aprodc	0.313**	−0.373**	0.313**	−0.364**	0.092	0.073
	cash	0.252*	−0.156	0.251*	−0.21	0.229	0.03
	cashdebt	0.899***	−0.724***	0.901***	−0.597***	0.748***	−0.451**
	cdind	0.349*	−0.328*	0.356**	−0.27	0.125	−0.133
	cf_var_mo	0.129	−0.465*	0.137	−0.383	0.161	−0.26
	ch_fc_acc	0.421***	0.025	0.423***	0.065	0.420***	−0.064
	cto	0.066	0.091	0.074	0.242	0.166	−0.029
	d2a	0.409*	−0.318	0.412*	−0.198	0.199	0.011
	del_cash1	0.165	0.014	0.163	−0.021	0.194*	−0.04
	diss	0.117	−0.113	0.12	−0.034	0.157*	−0.113
	dist_e	0.610***	−0.457**	0.615***	−0.339*	0.401***	−0.254*
	dpfs	0.244	−0.226	0.246	−0.254	0.201	−0.278
	dur	0.688***	−0.340*	0.691***	−0.284*	0.323**	−0.12
	dXFIN1	0.654***	−0.508**	0.658***	−0.410**	0.382***	−0.243*
	dXFIN2	0.806***	−0.742***	0.793***	−0.581***	0.470***	−0.403**
	e_cons	0.204	−0.139	0.207	−0.117	0.223*	−0.204
	earn_per	0.280**	−0.274*	0.278**	−0.294*	0.243*	−0.197
	earn_pred	0.617***	−0.223	0.617***	−0.225	0.691***	−0.410**
	gp	0.724***	−0.530**	0.726***	−0.445**	0.452***	−0.21
	ia	0.356**	−0.249	0.358**	−0.209	0.157	−0.076
	laborprod_ia	0.199*	−0.205	0.199*	−0.198	0.263**	−0.288*
	lag_ag	−0.106	0.02	−0.11	−0.053	0.048	−0.077
	ltprofit	0.649***	−0.523**	0.655***	−0.464**	0.466***	−0.344*
	margin	0.509***	−0.545***	0.510***	−0.526***	0.315**	−0.22
	nincr_up	0.348*	0.332*	0.351*	0.367*	0.247	0.225
	noa_lev	0.536***	−0.437**	0.539***	−0.383**	0.363**	−0.161
	nop_mo	0.834***	−0.601***	0.837***	−0.506**	0.803***	−0.515**
	ns	0.166	−0.229	0.167	−0.166	0.077	0.002
	ns_ti	0.236	−0.176	0.237	−0.14	−0.006	0.13
	nwc_chng	0.569***	−0.320*	0.570***	−0.306*	0.431***	−0.165

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Category	Anomaly	Raw Return α	Raw Return β	CAPM α	CAPM β	FF6 α	FF6 β
Fundamentals	op_ff	0.909***	−0.659***	0.910***	−0.619***	0.246**	−0.216*
	org_cap	0.157	−0.107	0.16	0.008	0.284**	−0.178
	pchcurrat	0.067	−0.121	0.068	−0.11	−0.016	−0.004
	pm	0.519***	−0.447**	0.519***	−0.475**	0.472***	−0.245
	rd_inc	−0.662	0.74	−0.66	0.768	0.192	0.076
	rna	0.723***	−0.586***	0.725***	−0.520***	0.396**	−0.151
	roaq	1.069***	−0.233	1.072***	−0.131	0.829***	−0.204
	roe_2	0.687***	−0.492**	0.688***	−0.458**	0.521***	−0.290*
	roic	1.045***	−0.839***	1.046***	−0.795***	0.599***	−0.380**
	rsup2	0.381**	0.164	0.382**	0.166	0.340**	−0.012
	sga_at	0.087	0.01	0.087	0.102	0.179	0.031
	std_emp	0.203	−0.123	0.208	0.003	0.408**	−0.261
	sue	0.521**	0.35	0.524**	0.377	0.558***	0.015
	tang	0.162	−0.03	0.163	0.027	0.135	0.033
	tang2	0.25	−0.155	0.249	−0.178	0.320*	−0.109
	tax1	0.235*	−0.133	0.236*	−0.117	0.173	−0.044
	usd_exp	0.071	0.121	0.07	0.115	0.146	0.079
Analyst	an_value	1.057***	−0.658**	1.054***	−0.698**	0.924***	−0.620**
	chnanalyst	−0.159	0.124	−0.161	0.17	−0.202*	0.219
	del_ltg	0.287*	−0.063	0.288*	−0.038	0.238	−0.01
	down_f	0.227*	0.182	0.230**	0.243*	0.065	0.230*
	efp	1.116***	−0.735**	1.113***	−0.778**	0.949***	−0.655***
	eps_disp	0.781**	−0.449	0.794***	−0.328	0.505**	−0.329
	ltg	0.575**	−0.653***	0.575***	−0.564***	0.397**	−0.370*
	re_1	0.354*	0.199	0.355**	0.249	0.273*	0.136
	up	0.271**	0.025	0.271**	0.013	0.170*	0.043
Undefined	failure	0.706**	−0.347	0.710***	−0.176	0.268	−0.102
	kz	0.802***	−0.590**	0.805***	−0.459**	0.599***	−0.423**
	oscore	0.881***	−0.917***	0.879***	−0.963***	0.718***	−0.558***
	qmj	0.601***	−0.578***	0.600***	−0.613***	0.402***	−0.252*
	shum	0.655**	−0.088	0.657**	0.001	0.457***	−0.252
	sin	0.271	−0.178	0.272*	0.061	0.278*	−0.119
	zscore	0.273	−0.550**	0.273	−0.485**	0.365**	−0.157
	Average	0.497	−0.227	0.498	−0.200	0.398	−0.138
Summary	# Sign. β (> 0)		10		14		10
	# Sign. β (< 0)		59		58		47
	# Non-sign. β		69		66		81

Table 5: **Regression analysis by anomaly category and region**

This table provides the results of the Carhart (1997) four-factor model alpha for 134 anomalies, calculated with value-weighted portfolios (5. quintile - 1. quintile), in relation to GOOD TIMES by anomaly category (Panel A) and region (Panel B). To take into account that we investigate the four-factor alpha and therefore control for MKTRF, SMB, HML, and WML, we exclude them from the regression and the summary statistics in the table. Each panel is separated into two parts. The second to sixth column represent the parameters for a panel regression with regard to the respective category or regional level (e.g., number of observations, intercept α, p-value of α, slope β, p-value of β). The other columns aggregate the results from individual anomalies. $\bar{\alpha}$ is the average intercept, $\bar{\beta}$ the average slope, $\bar{\beta}$ (> 0) and (< 0) stands for the average slope if the slope is positive or negative, respectively. # Sign. β (> 0) and (< 0) is the number of significant slopes with positive or negative sign at 5% level and # Non-sign. β is the number of non-significant slopes. We control for country effects and the standard errors are clustered with regard to the respective month. In addition, we include anomaly effects in the panel regression. The international sample for Panel A covers monthly anomaly returns from September 1981 until June 2019. We investigate the same period for the regions USA, Ex USA, DM, and EM. For FM, the sample starts at May 1993.

Panel A: Overview Anomaly Categories

	Category-wise					Anomaly-wise						
	N	α	p(α)	β	p(β)	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\beta}$ (> 0)	$\bar{\beta}$ (< 0)	# Sign. β (> 0)	# Sign. β (< 0)	# Non-sign. β
Model Factor	196,619	0.509***	0.000	−0.133**	0.003	0.513	−0.128	0.169	−0.227	1	5	10
Market	594,126	0.499***	0.000	−0.205***	0.000	0.515	−0.204	0.216	−0.414	4	20	21
Fundamentals	667,399	0.406***	0.000	−0.177***	0.000	0.400	−0.172	0.082	−0.233	0	16	35
Valuation	80,287	0.801***	0.000	−0.282**	0.007	0.776	−0.271	0.143	−0.354	0	4	2
Analyst	107,820	0.484***	0.000	−0.197*	0.011	0.445	−0.175	0.097	−0.392	1	3	5
Undefined	96,081	0.545***	0.000	−0.273**	0.003	0.543	−0.272	NA	−0.272	0	3	4

Panel B: Overview Regions

	Region-wise					Anomaly-wise						
	N	α	p(α)	β	p(β)	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\beta}$ (> 0)	$\bar{\beta}$ (< 0)	# Sign. β (> 0)	# Sign. β (< 0)	# Non-sign. β
USA	57,562	0.653***	0.000	−0.354**	0.003	0.642	−0.343	0.408	−0.674	3	32	99
Ex USA	1,684,770	0.478***	0.000	−0.190***	0.000	0.478	−0.186	0.160	−0.299	6	52	76
DM	983,161	0.473***	0.000	−0.238***	0.000	0.474	−0.236	0.185	−0.328	3	43	88
EM	602,166	0.513***	0.000	−0.162**	0.001	0.508	−0.150	0.298	−0.348	6	32	96
FM	157,005	0.459***	0.000	−0.019	0.823	0.446	0.009	0.401	−0.339	6	4	123

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 6: **Multivariate regression analysis**

This table corresponds to the measurements from Table 5 by anomaly category (Panel A) and region (Panel B) for the Carhart (1997) four-factor model alpha for 134 anomalies, calculated with value-weighted portfolios (5. quintile - 1. quintile). In addition to GOOD TIMES, we include a second indicator, UP, or news sentiment (MP) according to the following methodology:

$$r_{i,t} = \alpha_i + \beta_{GOOD,i} * MS_{GOOD,t} + \beta_{Control,i} * MS_{Control,t} + \sum_{n=1}^{4} \beta_{n,i} * r_{n,t} + f_{i,c} + (f_{i,a}) + \epsilon_{i,t}$$

If i represents a single anomaly, we only control for country effects $f_{i,c}$. For the panel regression, i represents a category and we include anomaly effects $f_{i,a}$. The standard errors are clustered with regard to the respective month. A column description can be found in Table 5. The international sample for Panel A covers monthly anomaly returns from September 1981 until June 2019. We investigate the same period for the regions USA, Ex USA, DM, and EM. For FM the sample starts at May 1993.

Panel A: Overview Anomaly Categories

		Category-wise			Anomaly-wise						
		α	β_{GOOD}	$\beta_{Control}$	$\bar{\alpha}$	$\bar{\beta}_{GOOD}$	$\bar{\beta}_{Control}$	# Sign. β_{GOOD} (>0)	# Sign. β_{GOOD} (<0)	# Sign. $\beta_{Control}$ (>0)	# Sign. $\beta_{Control}$ (<0)
UP	Model Factor	0.595***	−0.106*	−0.140**	0.601	−0.101	−0.144	1	4	0	5
	Market	0.553***	−0.194***	−0.084	0.554	−0.170	−0.085	4	18	0	4
	Fundamentals	0.488***	−0.148***	−0.136**	0.477	−0.144	−0.128	0	14	0	4
	Valuation	0.883***	−0.260*	−0.145	0.861	−0.249	−0.148	0	4	0	0
	Analyst	0.501***	−0.184*	−0.043	0.454	−0.164	−0.027	0	4	1	1
	Undefined	0.674***	−0.238**	−0.191	0.680	−0.264	−0.166	0	3	0	2
	Overall	0.551***	−0.170***	−0.117**	0.543	−0.159	−0.112	5	47	1	16
News Sentiment (MP)	Model Factor	0.484***	−0.093	−0.414**	0.487	−0.092	−0.414	1	5	0	3
	Market	0.488***	−0.185***	−0.305**	0.484	−0.161	−0.355	3	12	1	5
	Fundamentals	0.407***	−0.168***	−0.185	0.402	−0.165	−0.151	0	12	1	4
	Valuation	0.784***	−0.275*	−0.396	0.772	−0.272	−0.385	0	2	0	1
	Analyst	0.451***	−0.214*	−0.476*	0.429	−0.200	−0.466	0	3	0	2
	Undefined	0.488***	−0.193	−0.523*	0.524	−0.215	−0.471	0	2	0	2
	Overall	0.467***	−0.174***	−0.300**	0.464	−0.164	−0.297	4	36	2	17

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Table 6: **(continued)**

Panel B: Overview Regions

		Category-wise			Anomaly-wise						
		α	β_{GOOD}	$\beta_{Control}$	$\bar{\alpha}$	$\bar{\beta}_{GOOD}$	$\bar{\beta}_{Control}$	# Sign. β_{GOOD} (> 0)	# Sign. β_{GOOD} (< 0)	# Sign. $\beta_{Control}$ (> 0)	# Sign. $\beta_{Control}$ (< 0)
UP	USA	0.626***	−0.434**	0.106	0.618	−0.426	0.103	5	41	6	5
	Ex USA	0.554***	−0.166***	−0.125**	0.552	−0.162	−0.122	5	47	0	17
	DM	0.533***	−0.223***	−0.086	0.531	−0.220	−0.084	3	37	2	4
	EM	0.597***	−0.128*	−0.152**	0.589	−0.118	−0.148	6	25	3	14
	FM	0.561***	0.027	−0.226*	0.552	0.056	−0.240	6	4	1	12
News Sentiment (MP)	USA	0.586*	−0.384	−1.226	0.567	−0.368	−1.283	2	17	1	4
	Ex USA	0.465***	−0.169***	−0.293**	0.465	−0.167	−0.290	4	40	2	16
	DM	0.436***	−0.203**	−0.319*	0.437	−0.201	−0.317	4	19	2	13
	EM	0.491***	−0.125*	−0.366	0.488	−0.120	−0.363	7	22	1	9
	FM	0.461***	−0.017	0.190	0.444	0.015	0.133	2	8	3	1

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 7: **Regression analysis for the long- and short anomaly part**

This table provides the regression results for the 118 anomalies with significant α (5% level of significance) with regard to the good times indicator. Each anomaly can be considered as a long-short portfolio. Therefore, we separate the long- and short-part of the anomaly. Panel A gives the regression parameters based on the anomaly category, while Panel B is based on the region. Both sub-tables are separated into a panel regression for each characteristic and an aggregated summary of the regression results for every anomaly. In the panel regression N is the number of observations, α the intercept, $p(\alpha)$ the p-value for the intercept, β the slope, and $p(\beta)$ the p-value for the slope. In addition, $\bar{\alpha}$ is the average intercept, $\bar{\beta}$ the average slope, $|\bar{\alpha}|$ the average absolute intercept, $|\bar{\beta}|$ the average absolute slope, # Sign. β (>0) the number of significant slopes with positive sign, # Sign. β (<0) the number of sign. slopes with negative sign, and # Non-sign. β the number of non-significant slopes. For the latter, the 5% threshold is used as significance level. We control for the model factors of the FF4 and country effects. The panel regression additionally takes into account anomaly effects. The standard errors are clustered with regard to the respective month.

Panel A: Overview Anomaly Categories

		Category-wise					Anomaly-wise						
		N	α	p(α)	β	p(β)	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\beta}$ (>0)	$\bar{\beta}$ (<0)	# Sign. β (>0)	# Sign. β (<0)	# Non-sign. β
Long	Model Factor	201,769	0.165**	−0.006	0.191**	−0.002	0.166	0.193	0.220	−0.212	11	0	5
	Market	594,126	0.094**	−0.002	−0.118***	0.000	0.123	−0.125	0.254	−0.402	11	16	18
	Fundamentals	667,402	0.05	−0.108	0.019	−0.565	0.049	0.018	0.172	−0.320	9	11	31
	Valuation	80,308	0.298***	0.000	0.026	−0.719	0.291	0.026	0.138	−0.538	1	1	4
	Analyst	107,820	0.111**	−0.009	-0.041	−0.375	0.081	−0.050	0.117	−0.258	2	2	5
	Undefined	96,143	0.146**	−0.002	−0.149**	−0.006	0.147	−0.143	0.135	−0.513	0	3	4
Short	Model Factor	200,216	−0.270***	0.000	0.218***	−0.001	−0.283	0.214	0.301	−0.396	10	2	4
	Market	611,617	−0.406***	0.000	0.086***	−0.001	−0.395	0.079	0.404	−0.232	15	16	14
	Fundamentals	691,233	−0.355***	0.000	0.200***	0.000	−0.352	0.196	0.314	−0.150	32	5	14
	Valuation	81,103	−0.498***	0.000	0.302***	0.000	−0.486	0.297	0.404	−0.236	4	1	1
	Analyst	120,788	−0.374***	0.000	0.117**	−0.009	−0.373	0.122	0.341	−0.151	3	2	4
	Undefined	96,867	−0.400***	0.000	0.135**	−0.007	−0.397	0.133	0.258	−0.181	3	1	3

Panel B: Overview Regions

		Region-wise					Anomaly-wise						
		N	α	p(α)	β	p(β)	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\beta}$ (>0)	$\bar{\beta}$ (<0)	# Sign. β (>0)	# Sign. β (<0)	# Non-sign. β
Long	USA	57,562	0.094	−0.054	-0.087	−0.11	0.105	−0.108	0.274	−0.336	4	17	113
	Ex USA	1,690,006	0.100***	0.000	-0.017	−0.512	0.107	−0.021	0.197	−0.375	35	35	64
	DM	986,093	0.077**	−0.006	−0.064*	−0.032	0.093	−0.077	0.139	−0.286	10	28	96
	EM	603,604	0.130***	0.000	-0.002	−0.952	0.121	0.003	0.268	−0.376	28	27	79
	FM	157,871	0.117*	−0.038	0.216**	−0.003	0.110	0.238	0.585	−0.541	43	16	74
Short	USA	58,150	−0.558***	0.000	0.263**	−0.003	−0.538	0.235	0.386	−0.190	29	2	103
	Ex USA	1,743,674	−0.369***	0.000	0.159***	0.000	−0.365	0.154	0.344	−0.209	67	27	40
	DM	1,014,357	−0.394***	0.000	0.162***	0.000	−0.380	0.149	0.323	−0.154	51	19	64
	EM	621,149	−0.370***	0.000	0.149**	−0.002	−0.375	0.145	0.343	−0.246	48	19	67
	FM	166,318	−0.316***	0.000	0.200**	−0.005	−0.320	0.204	0.597	−0.470	38	28	67

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$